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# Venture capital investments and the technological performance of portfolio firms



Henry Lahr<sup>a,b,1</sup>, Andrea Mina<sup>c,\*</sup>

<sup>a</sup> Centre for Business Research, Cambridge Judge Business School, University of Cambridge, Trumpington Street, Cambridge CB2 1AG, UK

<sup>b</sup> Department of Accounting and Finance, The Open University, The Open University Business School, Walton Hall, Milton Keynes MK7 6AA, UK

<sup>c</sup> Cambridge Judge Business School, University of Cambridge, Trumpington Street, Cambridge CB2 1AG, UK

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## ABSTRACT

What is the relationship between venture capitalists' selection of investment targets and the effects of these investments on the patenting performance of portfolio companies? In this paper, we set out a modelling and estimation framework designed to discover whether venture capital (VC) increases the patenting performance of firms or whether this effect is a consequence of prior investment selection based on firms' patent output. We develop simultaneous models predicting the likelihood that firms attract VC financing, the likelihood that they patent, and the number of patents applied for and granted. Fully accounting for the endogeneity of investment, we find that the effect of VC on patenting is insignificant or negative, in contrast to the results generated by simpler models with independent equations. Our findings show that venture capitalists follow patent signals to invest in companies with commercially viable know-how and suggest that they are more likely to rationalise, rather than increase, the patenting output of portfolio firms.

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## 1. Introduction

New firms can rarely rely on internal cash flows in their pursuit of entrepreneurial opportunities. Among the sources of external finance available to entrepreneurs, venture capital (VC) can provide not only the financial resources they require, but also assistance to enhance the design, development, and performance of portfolio companies (Lerner, 1995; Bergemann and Hege, 1998; Gompers and Lerner, 2001; De Clercq et al., 2006; Schwienbacher, 2008; Cumming, 2010).

Among the different dimensions of entrepreneurial growth that the literature has noted, a strong association has been identified between VC investments and innovation, often measured by the firm's patenting output. A prominent thesis is that venture capitalists improve investee firms' innovative performance through their ability to 'coach' new businesses and to nurture them to produce greater technological output (Kortum and Lerner, 2000; Popov and Roosenboom, 2012). An alternative argument has received

relatively less attention as yet, although its validity may lead to a different conclusion: that venture capitalists are exceptionally good at identifying new firms with superior technological capabilities, which they see as the best investment opportunities. Seen from this angle, the most distinctive trait of VC, and therefore the most salient explanation for the stronger technological performance of VC-backed firms relative to other firms, would be the venture capitalists' superior selection capabilities (Baum and Silverman, 2004).

Venture capitalists face a resource allocation problem characterised by high risk and strong information asymmetries. In order to decrease these information asymmetries – given that potential investees have little or no track records of market performance – investors have to rely on other signals of firm quality. These include the *ex ante* patenting performance of potential investees (Häussler et al., 2012; Conti et al., 2013b; Hsu and Ziedonis, 2013), so patenting can be seen as an antecedent of VC investment decisions, as well as a likely consequence. Disentangling the relationship between VC investment and firms' technological performance involves a significant theoretical as well as empirical challenge because of endogeneity and reverse causation between the investment and innovation processes.

This is an important problem, not only from a scholarly perspective but also from a policy viewpoint. Even though the VC sector finances only a minority of new firms, it plays a very prominent

\* Corresponding author. Tel.: +44 1223 765330.

E-mail addresses: [h.lahr@cbr.cam.ac.uk](mailto:h.lahr@cbr.cam.ac.uk) (H. Lahr), [a.mina@jbs.cam.ac.uk](mailto:a.mina@jbs.cam.ac.uk) (A. Mina).

<sup>1</sup> Tel.: +44 1908 332648.

role in policies designed to overcome finance gaps and to grow entrepreneurial, innovation-driven economies (OECD, 2014). This role has not gone unquestioned: critical issues have been raised about scale and skills in the demand and supply of venture finance (Nightingale et al., 2009), governance (Lerner, 2009), cyclicity and stage distribution of investments (Kaplan and Schoar, 2005; Cumming et al., 2005; Lahr and Mina, 2014), and the overall returns and long-term sustainability of the VC investment model (Mason, 2009; Lerner, 2011; Mulcahy et al., 2012). These make it even more important to gain a clear and accurate understanding of the VC-innovation nexus.

In this paper we model the relation between VC and patenting using simultaneous equations to consider both the determinants of VC investments, including patents as signals of firm quality, and the effect of VC on firms' post-investment patenting performance, controlling for their prior performance. We use data from an original survey of 3669 US and UK companies. We extract information on the 940 firms that sought finance between the years 2002 and 2004 and match these records with patent data extracted from the European Patent Office's Worldwide Patent Statistical Database (PatStat) for the periods concurrent to and following the survey years. Controlling for other firm characteristics (e.g. size, age, R&D expenditure, and market size), we estimate simultaneous models for (1) the likelihood that firms' patenting activities predict VC investments and (2) the likelihood that such investments lead to patenting in the following period. We employ a bivariate recursive probit model and develop a simultaneous zero-inflated Poisson model for count data, using both to control for the endogenous nature of the selection and coaching processes.

We demonstrate that, once we account for endogeneity, the effect of VC on the subsequent patenting output of portfolio companies is either negative or insignificant. These results indicate that, while venture capitalists positively react to patents as signals of companies with potentially valuable knowledge, confirming the 'selection' hypothesis, there is no evidence of a positive effect of VC investment on firms' subsequent patenting performance. It is plausible that VC will positively influence other aspects of new business growth (i.e. commercialisation, marketing, scaling up, etc.), but the contribution of VC does not seem to involve increasing investee firms' technological outputs. Importantly, the fact that the technological productivity of a firm may slow down after VC investment does not imply that the firm would be better off without VC: on the contrary, an insignificant or negative effect of VC on firm patenting suggests that venture capitalists rationalise technological searches and focus the firm's finite resources, including managerial attention, on the exploitation of existing intellectual property (IP) rather than further technological exploration.

This paper advances our understanding of the financing of innovative firms by modelling the determinants of investment choices by VC and the patenting output of their portfolio companies at the time of and after VC investment. In so doing, the paper also introduces an original methodology that can disentangle the endogenous relationship between VC and patenting efficiently, and has the potential for further uses in treating analogous theoretical structures.

## 2. VC investments and patenting: Theory and evidence

Investments in small and medium-sized businesses, and in particular new technology-based firms, pose specific challenges to capital markets because they involve high risks and strong information asymmetries (Lerner, 1995; Hall, 2002). From an investor's viewpoint, the economic potential of these firms is difficult to assess given their short history and the lack of external signals about their quality (e.g. audited financial statements, credit

ratings), or of market feedback about new products and services at the time of investment. Only few investors are able and willing to back these businesses. They do so with the expectation of satisfactory returns by applying a specific set of capabilities, and often sector-specific business knowledge, that enable them to make better choices relative to competing investors, handle technological and market uncertainty, and actively influence the outcome of their investments (Sahlman, 1990; Gompers, 1995; Hellmann, 1998; Gompers and Lerner, 1999, 2001; Kaplan and Strömberg, 2003, 2004).

In the extant studies that have addressed the links between VC and innovation, one stream has focused on the ability of venture capitalists to assist portfolio companies by giving them formal and informal advice, thus adding value in excess of their financial contributions (Gorman and Sahlman, 1989; Sapienza, 1992; Busenitz et al., 2004; Park and Steensma, 2012). A second and more recent stream has instead emphasised the ability of VCs to use patents as signals of firm quality and to make superior choices, relative to other investors, among the investment options that are available to them. If what matters for the subsequent performance of portfolio companies is the quality of the initial investment decision, the source of venture capitalists' competitive advantage rests on their selection capabilities, defined as their ability to identify the investee companies with the greatest growth potential (Dimov et al., 2007; Yang et al., 2009; Fitza et al., 2009; Park and Steensma, 2012). In the following two sections we review the arguments and evidence behind these two perspectives.

### 2.1. The effects of VC on patenting

The proposition that venture capitalists are able to increase firm value beyond the provision of financial resources has gained considerable support in the literature (Gorman and Sahlman, 1989; Sahlman, 1990; Bygrave and Timmons, 1992; Lerner, 1995; Keuschnigg and Nielsen, 2004; Croce et al., 2013), and is especially clear when they are compared, for example, to banks in the supply of external financing to small and medium-sized enterprises (Ueda, 2004). Venture capitalists can take active roles in many aspects of the strategic and operational conduct of their portfolio firms, including the recruitment of key personnel, business plan development, and networking with other firms, clients and investors, often on the basis of in-depth knowledge of the industry (Florida and Kenney, 1988; Hellmann and Puri, 2000, 2002; Hsu, 2004; Sørensen, 2007).

Several studies find links between VC investments and firms' patenting performance, and generally interpret a positive association between the two as a result of the 'value-adding' or 'coaching' effects of VC. One of the most prominent studies on this topic is Kortum and Lerner's (2000) paper, in which the authors model and estimate a patent production function in an investment framework. Aggregating patent numbers by industry, they find a positive and significant effect of VC financing on (log) patent grants<sup>1</sup>. Ueda and Hirukawa (2008) show that these findings become even more significant during the venture capital boom in the late 1990s. However, estimations of total factor productivity (TFP) growth reveal that this was not affected by VC investment, a result that contrasts with Chemmanur et al.'s (2011) study, which reveals a positive effect of VC on TFP. Popov and Roosenboom (2012) also find similar positive, although weaker, results for such effects in European countries

<sup>1</sup> Both patenting and venture funding could be related to unobserved technological opportunities, thereby causing an upward bias in the coefficient on venture capital, but regressions that use information about policy shifts in venture fund legislation to construct an instrumental variable also show positive impacts of VC investments on patenting (Kortum and Lerner, 2000).

and industries. Further estimations of autoregressive models for TFP growth and patent counts by industry seem to suggest that TFP growth is positively related to future VC investment, but there is weaker evidence that VC investments precede an increase in patenting at the industry level, and there are indications that lagged VC investments are often negatively related to both TFP growth and patent counts (Hirukawa and Ueda, 2008).

Empirical firm-level studies on venture capital investments tend to confirm the existence of a positive relation between VC and patenting performance (Arqué-Castells, 2012; Bertoni et al., 2010; Zhang, 2009). This pattern is not only found for independent but also for corporate venture capital (Alvarez-Garrido and Dushnitsky, 2012; Park and Steensma, 2012). Lerner et al. (2011) estimate various models, including Poisson and negative binomial models, for patents granted and patent citations in firms that experienced private equity-backed leveraged buyouts (LBOs). They find an increased number of citations for patent applications post-LBO and no decrease in patent originality and generality after such investments. Patent counts do not seem to vary in a uniform direction. A study by Engel and Keilbach (2007) found that VC-backed firms apply for ten times as many patents as matched non-VC backed firms: the authors use propensity and balanced score matching to compare venture-funded to non-VC funded German firms in terms of their technological outputs and growth, although this difference was only weakly significant. Caselli et al. (2009) use a similar matching procedure to assess the difference in the patenting and growth performances in the venture-backed IPOs of Italian firms. Their results show a higher average number of patents in the venture-backed firms than in their control group. Importantly, however, none of these studies provides solutions to the fundamental problem of the endogeneity of investment relative to firms' technological performance<sup>2</sup>.

## 2.2. Investment selection

The second hypothesis that might explain the correlation between VC investment and firms' technological performance is that venture capitalists have distinctive selection capabilities. This implies a modelling framework in which the innovative profiles of potential investee firms affect the probability that they receive VC investment. From this perspective, patents can function as signals to investors about firm quality (Baum and Silverman, 2004; Mann and Sager, 2007; Häussler et al., 2012; Audretsch et al., 2012; Conti et al., 2013a,b; Hsu and Ziedonis, 2013).

There are several dimensions to the investment evaluation process employed by venture capitalists (Shepherd, 1999), and there is growing interest in the technological determinants of venture financing. Baum and Silverman (2004) explored the links between VC financing, patent applications, and patents granted. Their findings suggest that the amount of VC finance obtained depends on lagged patents granted and applied for, R&D expenditures, R&D employees, government research assistance, the amount of sector-specific venture capital, horizontal and vertical alliances, and the investee firm being a university spin-off. Age is negatively related to venture capital, as are net cash flows, diversification, and industry concentration. Mann and Sager (2007) confirm the positive impact of patenting on VC-related performance variables, including the number of financing rounds, total investment and exit status.

Similarly, a start-up firm's prior patenting attract greater amounts of VC funds in Cao and Hsu's (2011) study of venture-backed firms.

Häussler et al. (2012) elaborate on Spence's (2002) signalling theory to argue that the founders of entrepreneurial firms are better informed about the quality of the venture than are potential investors, and that they use patents as communication devices to bridge this information gap. Patents are effective signals of quality on the grounds that, as they are produced at a cost (in this case the fees associated with the patenting process), low-quality agents will tend to be weeded out. Their empirical analysis confirms that patent applications have a positive effect on the hazard rate of VC funding in a sample of British and German biotech companies. These findings resonate with prior results presented by Engel and Keilbach (2007), whose probit modelling of VC investment reveals a positive association with patents and the founder's human capital. Along a similar line of enquiry – albeit set in a broader Penrosian framework than that used by Häussler et al. (2012) – Hsu and Ziedonis (2013) analyse VC-financed start-ups in the US semiconductor sector. They show that, by bridging information asymmetries, patents increase the likelihood of obtaining initial capital from a prominent VC, and have positive effects on fundraising and IPO pricing (conditional on IPO exit).

By bringing these streams of contributions together, we aim to answer the question: Does venture capital positively contribute to the patenting performance of firms or is it a consequence of venture capitalists' ability to identify the best companies at the time of investment? Results based on firm-level information are mixed, which suggests that positive findings could be at least partially driven by VC's selection of companies on the basis of their current patent output. We can only shed light on the effects of coaching vis-à-vis the selection function of VC if we take into account the endogeneity of the relation between VC investment and the technological performance of firms. Our research strategy is therefore to model, test, and evaluate in a simultaneous setting (1) the effect of VC on the patenting performance of portfolio firms post investment and (2) the effect of firms' patenting performance on the probability of attracting VC.

## 3. Data and methodology

### 3.1. Data

This paper builds on a unique comparative survey of U.K. and U.S. businesses carried out jointly by the Centre for Business Research at the University of Cambridge and the Industrial Performance Center at MIT in 2004–2005. The basis for the sampling was the Dun & Bradstreet (D&B) database, which contains company-specific information drawn from various sources, including Companies House, Thomson Financial, and press and trade journals<sup>3</sup>. The sample covered all manufacturing and business service sectors, and was stratified by sector and employment size (10–19; 20–49; 50–99; 100–499; 500–999; 1000–2999; and 3000+), with larger proportions taken in the smaller size bands, as in both countries the vast majority (over 98%) of firms employ fewer than 100 people. The data were collected via telephone surveys between March and November 2004 (response rates: 18.7% for the U.S. and 17.5% for the U.K.), followed by a postal survey of large firms in spring 2005 leading to a total sample of 1540 U.S. firms and 2129 U.K. firms.

<sup>2</sup> To the best of our knowledge, Croce et al. (2013) is the closest attempt to date to address sample selection problems in the context of the value-added hypothesis. However, this interesting study does not consider any innovation indicators and its analysis of portfolio companies' productivity growth is limited by the use of only a small set of basic firm characteristics. Our paper does not focus on TFP estimates—instead we explore in some detail the technological output of firms in relation to entrepreneurial finance decisions.

<sup>3</sup> The choice of the Dun & Bradstreet database was motivated by its broad coverage of small firms, which are key for studying venture capital investments. Good coverage of SMEs is also the reason why the European Central Bank uses this database for its survey on the access to finance of SMEs in the euro area (SAFE); see <http://www.ecb.europa.eu/stats/money/surveys/sme/html/index.en.html>.



We restrict our sample to firms that actively sought finance during the two years prior to being interviewed, which produces a working sample of 940 firms (513 in the U.S. and 427 in the U.K.). The survey lists VC funds and business angels as possible sources of external finance. Despite some differences in stages and sizes of investments, geographic proximity, and motivation for investments (Ehrlich et al., 1994), both venture capitalists and angels spend considerable time with firms' management teams, and make substantial non-financial contributions in addition to their financial commitments, including working hands-on in their day-to-day operations (Kerr et al., 2014; Haines et al., 2003; Harrison and Mason, 2000). Since both formal and informal venture capitalists can perform similar functions from our study's viewpoint, we pool observations for these two classes of active investors, although when we perform robustness tests with separate samples, the results are consistent with our main analyses (Section 5.3). Information about the event of a VC investment enters our models as an endogenous binary variable.

Firms answered the survey questions almost completely, although minor gaps in the data would have prevented us from using about 10% of the survey responses. In order to avoid the loss of observations due to missing values, we use random regression imputation to approximate them (Gelman and Hill, 2006). The number of such imputations is generally very low—always less than 2% per variable. Where dependent variable values are missing, we drop those observations.

Patent data are taken from the European Patent Office's (EPO) Worldwide Patent Statistical Database (PatStat), which contains information on 68.5 million patent applications by 17.3 million assignees and inventors from 1790 to 2010. Since there are no firm identifiers available in PatStat, we match patent information to our survey data by firm name. We consider firms' global patent portfolios, and count all applications to different patent authorities for similar or overlapping know-how as multiple patenting events. To align patent data with the three year period addressed in the survey, we count the number of patents applied for and granted within a three-year period prior to the interview (calculated from exact survey response dates), and determine each firm's patenting status from this number. More specifically, we use application filing and publications dates for the first grant of an application to determine the timings of patenting events. For our dependent variables, we count applications and grants for the whole post-survey period in order to capture the long-term effects of VC investment. Finally, we include a dummy variable for the firm being based in the US or the UK to control for different propensities to patent – and likelihood of grant – in different domestic institutional environments. We abstain from using forward citation-weighted indicators for patents, a control for patent quality that is especially useful in studies of performance, because such citations may be affected by the likelihood of investment, and may thus introduce a further source of endogeneity into this analytical context that would be important to avoid.

Table 1 shows descriptive statistics for our sample firms' patenting activities and our independent variables. 146 firms from our sample applied for patents during the three-year survey period ( $t$ ), and 168 filed patent applications in the next period ( $t+1$ ). We identified patent grants in 115 and 141 firms in these respective periods. 96 firms gained venture capital or business angel financing in about equal proportions in the two years prior to the survey. A simple cross-tabulation of indicators for VC financing and for patenting activity at  $t$  (see Table 2) highlights the strong link between venture capital and patenting. It shows that 56.2% of VC-financed firms applied for patents in any of the periods, whereas only 18.2% of those without VC funding did so. But this picture begins to look different when we consider changes in the patenting status across periods. In the non-VC financed group, firms seem to start patenting

at time  $t+1$  more often than they stop applying after patenting at time  $t$ . In contrast, the numbers of firms in the VC-financed group that start patenting at time  $t+1$  balance those that discontinue their patenting activities after period  $t$ <sup>4</sup>. Including additional control variables in our multivariate analyses gives us a much more precise assessment of these state transitions.

The inclusion of explanatory variables builds on prior studies into the relationship between VC and patenting, which have often used a very limited number of co-determinants, sometimes only R&D expenditures. We extend the scope of the relevant predictors for the propensity to patent, of which R&D intensity is the preferred choice according to standard practice in the literature (Scherer, 1965, 1983; Pakes and Griliches, 1980; Pakes, 1981; Hausman et al., 1984). Since prior research has used various measures for this intensity, including the log of R&D expenditures, R&D expenditures scaled by size variables, or the number of R&D employees, we choose a suitable combination of these indicators. We proxy for size by taking the logarithm of employment and control for R&D intensity by including the percentage of R&D staff and a dummy indicating the presence of R&D expenditures. This allows us to avoid the use of multiple size-dependent measures, since variables enter the expected mean in Poisson specifications multiplicatively. Further variables control for age, country and industry. Following Scherer (1983), we use the amount of international sales to measure market size and control for industry concentration by the number of competitors. We measure CEO education by a dummy variable indicating whether the CEO has a university degree or not. The length of the average product development time in the firms' principal product market is also controlled for, since it arguably plays a role in attracting investment (Hellmann and Puri, 2000). Finally, given the highly cumulative nature of technical change (Dosi, 1988) we include lagged patent applications and grants as proxies for the firm's knowledge stocks that it uses to produce new patents<sup>5</sup>.

### 3.2. Models and estimation

The structure of firms' patenting decisions presents several econometric challenges. Previous research shows that the vast majority of firms do not patent, which causes observations of zero patents in a large proportion of firms leading in turn to model instability and error distributions that do not meet the model's assumptions if these excess zeroes are not properly addressed (Bound et al., 1984; Hausman et al., 1984). At the same time, unobservable heterogeneity is highly likely to be correlated between VC investment and patenting performance: for example, firms might disclose patenting activities to prospective investors, which increases the likelihood that we observe VC investments in combination with more patenting in the future. When using VC investment to explain patenting, this endogeneity complicates model estimation and may make it analytically intractable<sup>6</sup>.

We suggest that patenting involves a two-step process, in which firms first decide whether to use patenting as a suitable IP protection strategy and then produce patents according to a Poisson or similar distribution (see Fig. 1). Following this logic, we model patenting activity as a binary variable that depends on firm and industry characteristics and augment our models with an

<sup>4</sup> Less surprisingly, for patent grants the proportion of firms that start receiving grants compared with those that stop after receiving at least one grant in the previous period is higher for VC-funded firms.

<sup>5</sup> Inclusion of lagged dependent variables also helps to account for unobserved heterogeneity.

<sup>6</sup> A similar challenge, also associated with mixed empirical evidence, characterises studies of VC investments and the financial performance of portfolio companies. Confront, for example, Steier and Greenwood (1995) and Busenitz et al. (2004) with Fitza et al. (2009), and Matusik and Fitza (2012).

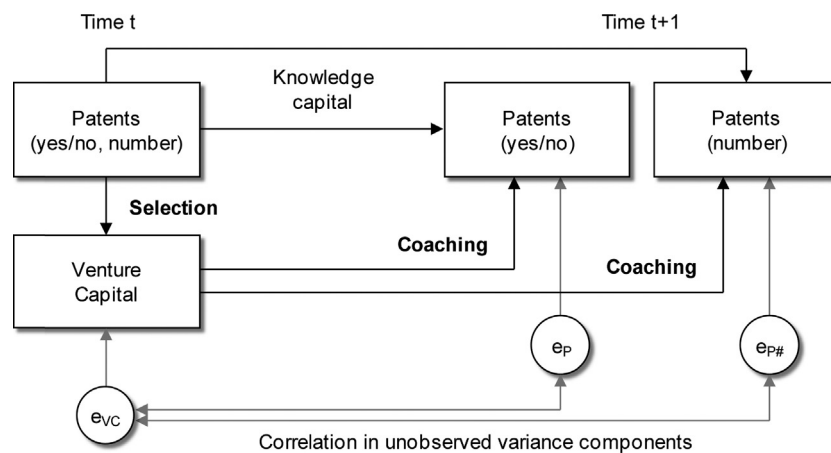
**Table 1**  
Descriptive statistics.

Variable	Mean	Median	Std. Dev.	Min	Max	Description
Any applications in $t+1$	0.179	0	0.383	0	1	
Patent applications in $t+1$	4.118	0	34.241	0	779	Number of patent applications by the firm in the period after the survey
Any grants in $t+1$	0.150	0	0.357	0	1	
Patent grants in $t+1$	2.746	0	30.337	0	889	Number of patent grants to the firm in the period after the survey
Any applications in $t$	0.155	0	0.362	0	1	
Patent applications in $t$	3.266	0	25.347	0	526	Number of patent applications by the firm in the period three years prior to the survey
Any grants in $t$	0.122	0	0.328	0	1	
Patent grants in $t$	1.176	0	9.972	0	273	Number of patent grants to the firm in the period three years prior to the survey
VC investment	0.102	0	0.303	0	1	The firm obtained formal or informal venture capital in the three-year period prior to the survey
Age (log)	2.937	2.996	0.858	0.693	5.720	The natural logarithm of the firm's age in years.
Size (log(employees))	3.848	3.714	1.059	1.099	6.804	The natural logarithm of the number of employees in the most recent financial year
U.S. firm	0.546	1	0.498	0	1	The firm has its headquarters in the United States. Dummy variable
Medium-high tech manuf.	0.310	0	0.463	0	1	The firm is a medium-high tech manufacturing firm according to the OECD (2005) Science, Technology and Industry Scoreboard
Medium-low tech manuf.	0.381	0	0.486	0	1	The firm is a medium-low tech manufacturing firm
R&D services & software	0.117	0	0.322	0	1	The firm is an R&D service or software firm.
Other services	0.153	0	0.360	0	1	The firm is a service firm other than R&D or software
Other industry	0.039	0	0.195	0	1	The firm operates under a SIC code not covered above
R&D expend. (yes/no)	0.732	1	0.443	0	1	The firm has R&D expenditures. Dummy variable
R&D staff	0.073	0	0.175	0	1	Full-time R&D staff as a proportion of total staff.
CEO has a degree	0.637	1	0.481	0	1	The firm's Chief Executive or MD has a degree. Dummy variable
Market size	1.747	2	0.912	0	3	Size of the firm's market. Coded as ordinal 0 = local, 1 = regional, 2 = national, 3 = international, treated as cardinal
Competitors (log)	1.987	1.792	1.012	0	6.909	Number of companies that the firm regards as serious competitors plus one, in logs
Product dev. time	0.971	1	1.048	0	4	Average time it takes to develop a new product from conception to the market. Coded as ordinal 0 = less than 6 months to 4 = more than 5 years, treated as cardinal

**Table 2**  
Venture capital and patenting status.

Applications in $t$	No VC ( $n=844$ ): Applications in $t+1$		VC ( $n=96$ ): Applications in $t+1$		No VC ( $n=844$ ): Grants in $t+1$		VC ( $n=96$ ): Grants in $t+1$	
	No (%)	Yes (%)	No (%)	Yes (%)	No (%)	Yes (%)	No (%)	Yes (%)
No	81.8	6.0	43.8	11.5	85.4	4.7	51.0	15.6
Yes	3.4	8.8	11.5	33.3	2.7	7.1	6.3	27.1

Notes. This table presents the fraction of firms in each present and future patenting status dependent on venture capital investment. Row entries are the number of firms with any number of patent applications at time  $t$ . Columns show the number of firms applying for or being granted any number of patents.



**Fig. 1.** Model framework. Notes. Dependent variables are venture capital investment at time  $t$  and the number of patent applications or grants at time  $t+1$ . In the binary bivariate case, "Patents (yes/no):" measures whether we observe any number of patents for the firm at time  $t+1$ . In zero-inflated Poisson models that also include the number of patents at  $t+1$ , this variable indicates firms' latent patenting status.

endogenous binary variable that indicates whether or not a firm receives venture capital financing. Instead of relying on propensity score matching or comparable algorithms to identify a control group of non-VC backed firms, we have the advantage that we can work with ‘treatment’ and ‘control’ data that are generated contemporaneously by the survey<sup>7</sup>. Our data allow us to identify firms that sought external finance, and those of them that obtained venture finance. The explicit consideration of finance-seeking behaviours, usually neglected in the literature, strengthens the quality of our sample and the precision of our results.

We estimate two sets of simultaneous equations: In the first set, which contains two probit equations for patenting and venture capital investments, we ignore information about the number of patents and treat firms’ patenting behaviours as binary outcomes. In the second set we introduce the number of patents in a zero-inflated Poisson model.

The patenting equation in the recursive bivariate system is

$$Pat_{i,t+1} = I(X_{it}\gamma_0 + \gamma_1 Pat_{it} + \gamma_2 \ln(PatN_{it}) + \theta^1 VC_{it} + \varepsilon_{it} > 0), \quad (1)$$

where  $Pat_{it}$  is a dummy variable indicating whether firm  $i$  applied for one or more patents or, depending on context, was granted at least one patent period  $t$ .  $PatN_{it}$  denotes the number of patent applications or patents granted. The indicator function  $I(\cdot)$  equals one if the condition in parentheses holds and zero otherwise. Since patent applications and grants can be zero – in which case the natural logarithm would not exist – we set  $\ln(PatN_{it})$  to zero and use a dummy variable ( $Pat_{it}$ ) to indicate patenting status. Endogenous venture capital investment is captured by an indicator variable ( $VC_{it}$ ), and  $X_{it}$  represents exogenous variables. The simultaneously determined venture capital investment is:

$$VC_{it} = I(Z_{it}\beta_0 + \beta_1 Pat_{it} + \beta_2 \ln(PatN_{it}) + v_{it} > 0), \quad (2)$$

where  $Z_{it}$  is a vector of exogenous explanatory variables which can contain some or all of the elements in  $X_{it}$ . Endogeneity of venture capital financing is accounted for by allowing arbitrary correlation between the error terms. Since variance of error terms is not identified in binary models, the error terms  $\varepsilon_{it}$  and  $v_{it}$  are normalised to have a variance of unity.

A similar simultaneous model structure can be used to predict the number of patents. Since patent data show a large number of non-patenting firms, we model this empirical regularity using a zero-inflated Poisson distribution. In this model, firms self-select into the patenting regime, and a third equation models the number of patent applications or grants produced according to a Poisson distribution. As in Lambert’s (1992) zero-inflated Poisson model, the number of patents is distributed as:

$$PatN_{i,t+1} = \begin{cases} 0 & \text{with probability } p_{it} + (1 - p_{it})e^{-\lambda_{it}} \\ k & \text{with probability } (1 - p_{it})e^{-\lambda_{it}} \lambda_{it}^k / k!, \quad k = 1, 2, \dots \end{cases} \quad (3)$$

<sup>7</sup> This approach differs from Park and Steensma’s (2012) and Conti et al.’s (2013b). In contrast to these studies, we have data on firms that received investment and firms that did not, because our sampling was not guided by VC investment events. This enables us to specify an appropriate test for selection (investment) instead of a test for the type of investment a firm may have received when all the firms in their sample have received some investments (i.e. where there is no counterfactual of ‘no VC investment’). Conti et al. (2013a), instead, have no-VC investment counterfactuals at their disposal, but their focus is different, as they are interested in the relative sensitivity of VC and business angel investors to heterogeneous investment signals. Moreover, they opt for a more traditional two-stage least squares linear probability model to treat endogeneity of investment.

The likelihood that a firm chooses *not* to patent in the next period is

$$p_{it} = I(X_{it}\gamma_0 + \gamma_1 Pat_{it} + \gamma_2 \ln(PatN_{it}) + \theta^1 VC_{it} + \varepsilon_{it}), \quad (4)$$

while the conditional mean of the Poisson process in the patenting state is

$$\lambda_{it} = \exp(X_{it}\delta_0 + \delta_1 Pat_{it} + \delta_2 \ln(PatN_{it}) + \theta^N VC_{it} + \omega_{it}) \quad (5)$$

A novel feature of our model is that a firm’s likelihood of obtaining venture capital is determined by an additional equation:

$$VC_{it} = I(Z_{it}\beta_0 + \beta_1 Pat_{it} + \beta_2 \ln(PatN_{it}) + v_{it} > 0) \quad (6)$$

as in the bivariate Probit case above.

We allow for arbitrary contemporaneous correlation between  $v_{it}$  and  $\varepsilon_{it}$ , as well as between  $v_{it}$  and  $\omega_{it}$ , which are assumed to follow bivariate normal distributions. Specifying the model in this way allows for correlation between heterogeneity in expected means of patent counts, the decision to patent and VC financing. The variance of individual-level errors ( $\omega_{it}$ ) introduces a free parameter that accounts for over-dispersion in Poisson models (Miranda and Rabe-Hesketh, 2006). Identification in semiparametric models of binary choice variables often relies on exclusion restrictions (Heckman, 1990; Taber, 2000)—in our parametric case, however, the functional form is sufficient for identification. In fact, imposing additional restrictions on our model could cause spurious results, since variables included in the VC equation but excluded from the patenting equations would affect the outcome equation through  $VC_{it}$  if those variables were not truly independent from patenting. We therefore choose the exogenous variables to be identical in all equations ( $X_{it} = Z_{it}$ ). Section 5.4 describes additional results obtained from robustness tests that use exclusion restrictions in the patenting equation(s).

In the following section we present the results of bivariate recursive probit models for VC financing and patenting (i.e., results for the simultaneous estimation of Eqs. (1) and (2) and then the results we obtain from the system of equations complete with the zero-inflated Poisson model (i.e., Eqs. (3) to (6)), estimated by maximum simulated likelihood (Gouriéroux and Monfort, 1996; Train, 2009)<sup>8</sup>. We also report results of zero-inflated Poisson models that include information about the number of patents, but exclude simultaneous VC investment as our baseline results for the complete system of equations (see Table 5). As terms of comparisons and to show how key results differ when endogeneity is not taken into account, we include results of independent (single-equation) probit models as robustness checks (Table 6).

#### 4. Results

We find that the correlations between venture capital investment and subsequent patenting are substantial and highly significant, ranging between 0.21 for (log) patent applications and 0.26 for a dummy variable measuring whether a firm was granted any patents after receiving VC investment. This positive link could be due to technological coaching or selection. As we construct increasingly complete models for the relation between VC investment and patenting, the coaching effect disappears. Table 3 presents the results from our simultaneous model that jointly predicts patenting and venture capital investment.

<sup>8</sup> We use subscripts  $t$  and  $t+1$  to distinguish between the periods concurrent to and following the survey. We use 200 random draws in all models estimated by maximum simulated likelihood. Further estimation details, including likelihood function and MSL methodology, are available from the authors.

**Table 3**  
Patenting and VC investment—simultaneous equations.

Dependent variable in patenting equation	Applications in $t + 1$		Grants in $t + 1$		Grants in $t + 1$	
Model	1		2		3	
Dependent variable in patenting equation	Patenting (yes/no)	VC investment	Patenting (yes/no)	VC investment	Patenting (yes/no)	VC investment
VC investment	–0.673 (0.34)**		–0.175 (0.52)		–0.444 (0.37)	
Patent applications (log)	0.455 (0.12)***	–0.095 (0.08)			0.568 (0.13)***	–0.098 (0.08)
Patent applications > 0	1.059 (0.21)***	0.609 (0.20)***			1.635 (0.22)***	0.614 (0.20)***
Patent grants (log)			0.534 (0.16)***	–0.170 (0.12)		
Patent grants > 0			1.206 (0.22)***	0.434 (0.23)*		
Age (log)	0.083 (0.08)	–0.344 (0.09)***	0.010 (0.11)	–0.344 (0.09)***	0.088 (0.10)	–0.342 (0.09)***
Size (log(employees + 1))	0.155 (0.06)***	0.197 (0.07)***	0.058 (0.07)	0.213 (0.07)***	0.027 (0.07)	0.206 (0.07)***
U.S. firm	0.053 (0.14)	–0.334 (0.13)**	0.279 (0.17)*	–0.327 (0.14)**	0.320 (0.18)*	–0.332 (0.14)**
Medium-high tech manuf.	0.095 (0.29)	–0.226 (0.29)	–0.084 (0.34)	–0.203 (0.30)	–0.254 (0.27)	–0.251 (0.28)
Medium-low tech manuf.	–0.223 (0.30)	–0.375 (0.29)	–0.463 (0.35)	–0.389 (0.29)	–0.566 (0.28)**	–0.400 (0.29)
R&D services & software	–0.131 (0.33)	0.271 (0.30)	–0.152 (0.40)	0.276 (0.30)	–0.260 (0.35)	0.267 (0.29)
Other services	0.068 (0.32)	–0.098 (0.31)	–0.757 (0.40)*	–0.127 (0.31)	–0.782 (0.36)**	–0.132 (0.31)
R&D expend. (yes/no)	0.468 (0.18)***	0.424 (0.21)**	0.318 (0.20)	0.439 (0.21)**	0.467 (0.21)**	0.425 (0.22)*
R&D staff (in %)	0.356 (0.35)	0.701 (0.33)**	0.755 (0.44)*	0.838 (0.32)***	–0.134 (0.44)	0.650 (0.33)**
CEO has a degree	0.145 (0.14)	0.363 (0.17)**	–0.201 (0.16)	0.347 (0.17)**	–0.214 (0.17)	0.344 (0.17)**
Market size	0.260 (0.09)***	0.191 (0.09)**	0.319 (0.10)***	0.203 (0.09)**	0.280 (0.11)***	0.206 (0.09)**
Product dev. time	0.160 (0.06)***	0.043 (0.07)	0.138 (0.06)**	0.055 (0.07)	0.120 (0.07)	0.045 (0.07)
Competitors (log)	–0.125 (0.06)**	–0.084 (0.08)	–0.119 (0.06)*	–0.087 (0.08)	–0.203 (0.07)***	–0.075 (0.07)
Intercept	–3.070 (0.46)***	–1.845 (0.44)***	–2.313 (0.54)***	–1.903 (0.43)***	–2.408 (0.52)***	–1.905 (0.44)***
Observations	940		940		940	
Log-Likelihood	–486.4		–454.7		–393.3	
Chi-sq. test	354.1		296.1		374.8	
P-value	0.000		0.000		0.000	
$\rho(v_{it}, e_{it})$						
p-Value for $\rho$ (Wald test)	0.010		0.130		0.002	
Pseudo- $R^2$	0.334		0.357		0.444	

Notes. This table presents bivariate recursive probit models for patent applications, patent grants and for the likelihood of observing venture capital investments. Robust standard errors are in parentheses.

Significance levels: \*\*\*  $p < 0.01$ ; \*\*  $p < 0.05$ ; \*  $p < 0.1$ .

#### 4.1. Patenting

Venture capital does not increase patenting activity (Table 3—first column of Models 1–3)—rather, it decreases the likelihood of a firm filing patent applications after the investment, in contrast to prior firm level (e.g. Arqu -Castells, 2012) and industry level studies (e.g. Kortum and Lerner, 2000) that found positive associations. The effect on future patent grants is insignificant. Correlations of unobserved effects in the patenting and selection equations are positive, supporting our modelling strategy.

We find strong persistence in patenting, for both applications and grants. If firms patent in one period, it tends to do so in the next. An indicator for prior-period patenting is significant in all specifications, while applying for or receiving a large number of patents in one period increases the likelihood of observing at least one patent in the next. These effects can be interpreted in two ways: On the one hand, prior patenting can be a proxy for unobserved heterogeneity between firms in their ability to produce innovations (other variables in our models might not capture all aspects of firms' internal processes and external market characteristics that lead to patenting behaviour). On the other hand, knowledge – in the form of existing patents – is an input for new patents. Existing patents can signal the size of firms' knowledge stocks, which are otherwise difficult to measure. As these productive capacity stocks depreciate over time, it is reasonable to assume that recent additions to the patent stock are the best predictors of present and future patenting activities, which is essentially what we find.

Strong evidence of the productivity effects of R&D expenditures is consistent with prior studies (Cohen, 2010). The percentage of R&D staff weakly predicts patenting activity, only showing positive coefficients in model 2. Human capital – as measured by the CEO's education – does not appear to increase the likelihood of

patent applications or grants. Firm age does not seem to affect patenting<sup>9</sup>, while firm size has a positive effect on future applications, but no effect on grants, as Bound et al. (1984) found. Other variables do not explain the variations in patenting that size would explain if they were excluded. Collinearity is low in our models (variance inflation factors are well below 5), and dropping significant variables from the models does not significantly change the effect of size. Industry effects collectively explain patenting, but on their own are only weak predictors. Significant Wald tests confirm the importance of controlling for industry effects. However, individual effects are rarely significant in our patenting models, as might be expected, since our estimations include detailed firm-level variables such as R&D and human capital. Unsurprisingly, firms categorised as medium-high technology manufacturing tend to apply for patents more often and obtain grants more frequently than low-tech manufacturing and service firms.

Firms based in the U.S. exhibit a higher chance of success (in terms of their applications being granted) than those located in the U.K., an indication of known institutional differences between the two countries' patenting regimes<sup>10</sup>. As expected, patenting activity is strongly associated with product market characteristics. Firms that operate nationally or internationally are more likely to engage in formal IP protection than local or regional firms. There is

<sup>9</sup> If patenting was to depend on firm age, we would expect a start-up effect early in the life of firms that are founded to exploit some technological opportunity. We tried a dummy variable indicating whether a firm was only founded during the sample period but found no influence on patenting activity.

<sup>10</sup> The non-obviousness standard in U.S. patent law at the application stage has been weakened, leading to the grant of patents on increasing numbers of trivial inventions (Barton, 2003; Galli ni, 2002). Structural differences in patenting processes also affect patent opposition, re-examination and revocation rates, which are significantly higher for European and U.K. patents than for U.S. patents (Harhoff and Reitzig, 2004; Graham et al., 2002).



little difference between models for future applications and grants. Products that need long lead development times are more often protected by patents than those with a short time to market. Again, this is reasonable from the viewpoint of a firm that needs more protection over longer R&D cycles. Finally, protection from imitation should be more prominent in industries characterised by intense competition, although it is possible that firms in concentrated markets try to deter entry through the strategic use of patenting (Scherer, 1983). While Scherer (1983) only finds evidence for a link between industry concentration and the number of patents in models that do not control for sectors, Baum and Silverman (2004) find fewer patents in concentrated industries. In contrast, the effect of high competition on patenting is negative in our models<sup>11</sup>.

#### 4.2. VC investment

A firm's knowledge stock is a good predictor of venture capital investment (see Table 3). Patenting attracts VC investments—more specifically, it is the fact that a company is patent-active, not the number of applications or grants, that predicts VC investment. Results are particularly strong for the application indicator, which signals strong innovation potential in portfolio companies.

R&D expenditures and R&D staff levels are both strong predictors of VC investments, as is the CEO's education level. VC involvement is more likely to be found in young firms, echoing the findings of prior research. Interestingly, however, venture capital funds appear to invest in larger firms more often than in smaller ones. This finding can be explained by interpreting size as a measure of investment risk, with very small firms typically being more opaque than larger ones. But it is also important to bear in mind that our sample includes firms with 10 to 1000 employees, and is therefore a sample of SMEs, as demanded for a study of VC investment. Industry effects point to a preference among venture investors for R&D services or software. Firms operating in larger (international) markets seem to be attractive investments, while coefficients for the intensity of competition are insignificant. Firms with long product development times are neither more nor less likely to gain venture capital<sup>12</sup>.

#### 4.3. Two-stage patenting—Patent counts, patenting, and venture capital

The large number of zeroes in patent counts suggests that patenting is a two-stage process, consisting of the binary decision whether to use patenting as an IP protection strategy and a decision about how many patents to apply for. Two popular methods used to model the number of patents produced by such processes are based on a zero-inflated Poisson distribution and a zero-inflated negative binomial distribution. In order to further refine our findings we integrate a zero-inflated Poisson process in our system of equations, which now includes an equation for patent counts, one for patenting, and one for venture capital investment. Table 4 presents the results for these estimations. For completeness, we include results

from a model with only the patent counts and patenting equations as Table 5, which provides the baseline for the full (three-equation) model discussed in this section.

The positive effect on firms' latent patenting states, which would be expected if venture capitalists added to their patenting performance, disappears across all models, while the negative effect on the number of granted patents remains. Moreover – and as in the simultaneous binary patenting models – the number of patent applications drops after VC investments.

If we look at the number of patents being applied for or granted, our results support the view that VC finance follows patent signals to invest in companies with existing commercially viable know-how. While the effect of VC investment on both the use of patents and on their numbers seems negligible, VC has a negative impact on patent grants and applications in some models. Venture capitalists are attracted to firms that produce patents, but do not contribute to the expansion of firms' knowledge stocks—instead, they are likely to shift firm resources from producing new patent applications to exploiting existing knowledge.

Control variables for future patent counts behave mostly as expected, and give further insights into firms' patenting decisions. While manufacturing firms and service firms appear – perhaps counterintuitively – equally likely to patent (see model 1 in Table 3), we find that being a manufacturing or R&D firm increases the number of patent applications relative to other service firms (see model 1 in Table 4). The estimation algorithm for three simultaneous equations picks the relevant equations for our two R&D variables: The existence of R&D programmes mainly predicts patenting in general, while the proportion of R&D staff explains the number of applications and grants awarded. In line with Baum and Silverman's (2004) results, we find that competition has a negative impact on the decision to patent (in bivariate models in Table 3) and the number of patents applied for or granted (in trivariate models in Table 4). However, firms tend to protect their position in the market by choosing to patent if their markets are large or have long product development times.

Estimated model parameters provide support for modelling VC investment, patenting, and the number of patents simultaneously. In most of the models tested for patent applications and grants, error correlations between the first (VC) equation and the second and third are substantial and significant. External shocks leading to VC investment correlate with the likelihood to patent with the expected positive sign (and negative sign for *not* patenting). Estimated error correlations between VC investment and patent numbers are again large and significant. We also test model stability by checking influential observations and cross-tabulations for firms that start or stop their patenting activities depending on VC investment, but find no abnormalities.

## 5. Robustness tests

### 5.1. Independent equations

Our first robustness check shows the advantages of our estimation strategy over simpler alternatives. We compare the results of our simultaneous estimations with those obtained from independent regressions for VC investment and patenting (see Table 6). While there is no change in the VC equation, there is a striking difference in the patenting equations (Table 6, columns 1–3): Without controlling for endogeneity, venture capital appears to increase the likelihood of patents being granted. This arguably biased result not only disappears in the simultaneous estimation strategy, but the finding emerges that VC investment can reduce the likelihood that firms apply for new patents in the period immediately after the investment. We can rule out that reduced effects of venture

<sup>11</sup> We also test the hypothesis that competition is more relevant if the firm operates internationally, but do not find that this interaction effect is significant. Prior studies have found conflicting evidence on the impact of profitability on patenting: Bertoni et al. (2010) show a positive relation between net cash flow and patents, whereas Baum and Silverman (2004) report a negative one. We also tried using a proxy for profitability constructed from pre-tax profits scaled by assets, but did not find significant results. Consequently, we decided to drop this variable from our models, due to the large amount of missing values in survey responses on profits.

<sup>12</sup> Although collinearity is not a problem in these models, there is some correlation between product development time and R&D efforts, which causes development time to become a significant predictor of VC investments if R&D variables are dropped from the regression.

**Table 4**  
Patenting, patent numbers, and VC investment.

Dependent variable in patenting equations	Applications in $t+1$		Grants in $t+1$		Grants in $t+1$	
Model	1		2		3	
Dependent variable	Not patenting (zero inflation)	VC investment	Not patenting (zero inflation)	VC investment	Not patenting (zero inflation)	VC investment
VC investment	0.186 (0.58)		–0.976 (0.66)		–0.815 (0.85)	
Patent applications (Log)	–0.313 (0.22)	–0.083 (0.08)			–0.371 (0.18)**	–0.103 (0.08)
Patent applications >0	–1.779 (0.51)***	0.560 (0.20)***			–2.460 (0.43)***	0.591 (0.20)***
Patent grants (Log)			–0.586 (0.21)***	–0.173 (0.13)		
Patent grants >0			–1.110 (0.27)***	0.400 (0.24)*		
Age (Log)	–0.161 (0.12)	–0.346 (0.10)***	–0.233 (0.12)*	–0.343 (0.09)***	–0.111 (0.14)	–0.338 (0.09)***
Size (log(employees + 1))	–0.167 (0.09)*	0.206 (0.07)***	–0.006 (0.08)	0.203 (0.07)***	0.022 (0.10)	0.201 (0.07)***
U.S. firm	0.075 (0.20)	–0.342 (0.13)**	–0.400 (0.18)**	–0.318 (0.14)**	–0.351 (0.24)	–0.342 (0.14)**
Medium-high tech manuf.	–0.151 (0.44)	–0.216 (0.29)	–0.061 (0.38)	–0.125 (0.30)	0.162 (0.36)	–0.228 (0.29)
Medium-low tech manuf.	0.188 (0.45)	–0.375 (0.29)	0.295 (0.39)	–0.346 (0.30)	0.465 (0.34)	–0.384 (0.29)
R&D services & software	0.159 (0.49)	0.280 (0.30)	–0.094 (0.48)	0.320 (0.30)	–0.111 (0.42)	0.266 (0.30)
Other services	–0.652 (0.57)	–0.107 (0.31)	0.634 (0.46)	–0.074 (0.32)	0.711 (0.49)	–0.116 (0.31)
R&D expend. (yes/no)	–0.613 (0.25)**	0.425 (0.21)**	–0.288 (0.23)	0.440 (0.21)**	–0.487 (0.28)*	0.432 (0.21)**
R&D staff (in %)	0.359 (0.51)	0.752 (0.32)**	–0.485 (0.56)	0.881 (0.32)***	1.123 (0.67)*	0.665 (0.33)**
CEO has a degree	–0.282 (0.22)	0.345 (0.17)**	0.313 (0.22)	0.333 (0.17)*	0.355 (0.23)	0.341 (0.17)**
Market size	–0.366 (0.14)***	0.186 (0.09)**	–0.299 (0.13)**	0.199 (0.09)**	–0.388 (0.15)***	0.194 (0.09)**
Product dev. time	–0.176 (0.09)*	0.045 (0.07)	–0.208 (0.10)**	0.052 (0.07)	–0.226 (0.11)**	0.050 (0.07)
Competitors (Log)	0.109 (0.09)	–0.081 (0.07)	0.148 (0.09)	–0.087 (0.07)	0.164 (0.11)	–0.082 (0.07)
Intercept	3.655 (0.70)***	–1.859 (0.44)***	2.780 (0.62)***	–1.897 (0.44)***	2.703 (0.65)***	–1.867 (0.44)***

Dependent variable	Applications (number)	Grants (number)	Grants (number)
VC investment	–0.780 (0.15)***	–0.136 (0.25)	–0.886 (0.29)***
Patent applications (Log)	0.815 (0.05)***		0.962 (0.05)***
Patent applications > 0	–0.160 (0.23)		–0.411 (0.32)
Patent grants (log)		0.615 (0.06)***	
Patent grants > 0		0.820 (0.23)***	
Age (log)	–0.032 (0.06)	–0.441 (0.12)***	–0.042 (0.11)
Size (log(employees + 1))	0.017 (0.05)	0.186 (0.09)**	0.014 (0.10)
U.S. firm	0.289 (0.10)***	–0.061 (0.15)	0.119 (0.19)
Medium-high tech manuf.	–0.027 (0.34)	–0.246 (0.27)	0.074 (0.40)
Medium-low tech manuf.	0.071 (0.36)	–0.282 (0.32)	0.130 (0.44)
R&D services & software	–0.106 (0.34)	–0.799 (0.30)***	–0.199 (0.45)
Other services	–1.136 (0.53)**	–0.664 (0.46)	–0.285 (0.59)
R&D expend. (yes/no)	0.224 (0.42)	–0.128 (0.41)	0.544 (0.32)*
R&D staff (in %)	1.215 (0.12)***	0.850 (0.30)***	1.059 (0.37)***
CEO has a degree	–0.158 (0.17)	0.012 (0.34)	0.031 (0.20)
Market size	–0.055 (0.09)	0.166 (0.11)	–0.211 (0.12)*
Product dev. time	0.096 (0.05)**	–0.103 (0.06)	–0.054 (0.07)
Competitors (log)	–0.210 (0.05)***	0.042 (0.14)	–0.239 (0.09)***
Intercept	0.259 (0.62)	0.914 (0.53)*	0.531 (0.53)
Var( $\omega_{it}$ )	1.307 (0.12)***	0.656 (0.10)***	0.483 (0.07)***
$\rho(v_{it}, \varepsilon_{it})$	–0.338 (0.24)*	0.076 (0.29)	–0.092 (0.44)
$\rho(v_{it}, \omega_{it})$	0.290 (0.03)***	–0.108 (0.06)**	0.444 (0.11)***
Observations	940	940	940
Wald test	25697	25356	8424
p-Value	0.000	0.000	0.000
Log-likelihood	–968.4	–846.0	–762.8

Notes. This table presents zero-inflated Poisson models for patent applications and patent grants during the period following the survey period, including an endogenous equation for venture capital investment. Robust standard errors (estimated using the sandwich estimator) are shown in parentheses.

Significance levels: \*\*\*  $p < 0.01$ ; \*\*  $p < 0.05$ ; \*  $p < 0.1$ .

capital are caused by estimation uncertainty due to the additional parameter for error correlation between equations. Wald tests of the joint significance of this correlation and the coefficient of venture capital on patenting are significant at the five percent level in all models in Table 3. The impact of positive error correlations can be seen in the coefficients for venture capital, which change considerably when estimated simultaneously. Introducing cross-equation correlation also harmonises coefficients for some variables across models and causes no major changes in the results for control variables.

Whether or not a firm obtains finance could have an impact on its ability to start or sustain patenting activities. Since we perform our regressions on a sample of firms that sought external finance, rather than only on those that obtained it, we add a set of robustness tests for this subsample. Results of separate regressions

(not reported here) confirm our findings in Table 3. However, two small changes appear in the patenting equations. First, the effect size of development time decreases slightly and loses its significance. Second, coefficients on product market competition all increase in magnitude, and the one predicting future applications becomes slightly significant. Estimating our models on the full dataset (including those 96 firms that did not obtain external finance) has two advantages over the smaller sample. First, adding these observations increases the statistical precision of our results. Second, our findings are conservative, that is, the effect of obtaining venture capital on patenting can be upward biased if it includes a (positive) effect of obtaining any kind of finance, which would be ignored if firms gaining no finance were excluded. In this sense, the negative or insignificant coefficients for venture capital represent upper bounds for the 'true' effect.

**Table 5**  
Patenting and patent numbers—zero-inflated Poisson model.

Dependent variable in patenting equations	Applications in $t+1$		Grants in $t+1$		Grants in $t+1$	
Model	1		2		3	
Dependent variable	Patents (number)	Not patenting (zero inflation)	Patents (number)	Not patenting (zero inflation)	Patents (number)	Not patenting (zero inflation)
VC investment	−0.503 (0.29) <sup>*</sup>	−0.342 (0.22)	−0.287 (0.22)	−0.689 (0.22) <sup>***</sup>	−0.696 (0.26) <sup>***</sup>	−1.130 (0.36) <sup>***</sup>
Patent applications (log)	0.805 (0.10) <sup>***</sup>	−0.448 (0.14) <sup>***</sup>			0.990 (0.09) <sup>***</sup>	−0.419 (0.18) <sup>**</sup>
Patent applications > 0	−0.756 (0.34) <sup>**</sup>	−1.150 (0.27) <sup>***</sup>			−0.916 (0.43) <sup>**</sup>	−2.372 (0.37) <sup>***</sup>
Patent grants (log)			0.682 (0.11) <sup>***</sup>	−0.545 (0.16) <sup>***</sup>		
Patent grants > 0			0.314 (0.30)	−1.167 (0.24) <sup>***</sup>		
Age (log)	−0.098 (0.17)	−0.177 (0.08) <sup>**</sup>	−0.318 (0.17) <sup>*</sup>	−0.143 (0.10)	0.143 (0.15)	−0.078 (0.14)
Size (log(employees + 1))	−0.125 (0.14)	−0.150 (0.07) <sup>**</sup>	0.244 (0.14) <sup>*</sup>	0.019 (0.07)	−0.138 (0.15)	−0.015 (0.10)
U.S. firm	0.401 (0.34)	−0.073 (0.16)	0.583 (0.24) <sup>**</sup>	−0.262 (0.16)	0.164 (0.17)	−0.381 (0.22) <sup>*</sup>
Medium-high tech manuf.	0.260 (0.32)	−0.159 (0.34)	−0.510 (0.58)	−0.041 (0.37)	−0.269 (0.46)	0.101 (0.34)
Medium-low tech manuf.	0.126 (0.36)	0.133 (0.34)	−0.162 (0.59)	0.390 (0.37)	−0.223 (0.47)	0.372 (0.33)
R&D services & software	0.392 (0.40)	0.255 (0.38)	−0.443 (0.62)	0.163 (0.42)	−0.459 (0.47)	−0.128 (0.40)
Other services	−0.498 (0.43)	−0.232 (0.37)	−0.415 (0.67)	0.726 (0.42) <sup>*</sup>	−0.684 (0.62)	0.696 (0.45)
R&D expend. (yes/no)	0.470 (0.39)	−0.420 (0.19) <sup>**</sup>	−0.100 (0.57)	−0.284 (0.23)	0.389 (0.45)	−0.484 (0.26) <sup>*</sup>
R&D staff (in %)	1.324 (0.72) <sup>*</sup>	−0.020 (0.37)	0.752 (0.48)	−0.474 (0.46)	1.551 (0.42) <sup>***</sup>	1.292 (0.62) <sup>**</sup>
CEO has a degree	−0.048 (0.28)	−0.105 (0.16)	−0.193 (0.32)	0.234 (0.18)	0.249 (0.35)	0.459 (0.25) <sup>*</sup>
Market size	0.055 (0.32)	−0.243 (0.09) <sup>***</sup>	0.487 (0.22) <sup>**</sup>	−0.233 (0.11) <sup>**</sup>	−0.157 (0.17)	−0.336 (0.15) <sup>**</sup>
Product dev. time	−0.225 (0.10) <sup>**</sup>	−0.189 (0.07) <sup>***</sup>	−0.072 (0.10)	−0.161 (0.08) <sup>**</sup>	−0.248 (0.09) <sup>***</sup>	−0.281 (0.11) <sup>**</sup>
Competitors (log)	−0.163 (0.15)	0.101 (0.07)	−0.307 (0.18) <sup>*</sup>	0.046 (0.09)	−0.568 (0.22) <sup>**</sup>	0.069 (0.14)
Intercept	1.674 (1.21)	3.451 (0.50) <sup>***</sup>	0.498 (1.11)	2.385 (0.55) <sup>***</sup>	1.974 (0.90) <sup>**</sup>	2.967 (0.65) <sup>***</sup>
Observations	940		940		940	
Wald test	2204.7		469.0		480.9	
p-Value	0.000		0.000		0.000	
Log-likelihood	−1537.8		−982.8		−819.3	

Notes. This table presents zero-inflated Poisson models for patent applications and patent grants during the period after the survey. When comparing coefficients from the patenting equation with prior models for the likelihood to patent, all signs must be reversed as the “patenting” equation in this table predicts the likelihood of *not* patenting. As a robustness test, we tried zero-inflated negative binomial models. Tests for overdispersion are all insignificant in these models, while Vuong tests against the alternative hypothesis of a standard Poisson process are highly significant. Robust standard errors are in parentheses.

Significance levels: \*\*\*  $p < 0.01$ ; \*\*  $p < 0.05$ ; \*  $p < 0.1$ .

**Table 6**  
Patenting activity and venture capital investment—dependent equations.

Model	Patenting (yes/no)			VC investment		
	1	2	3	4	5	6
Dependent variable	Applications in $t+1$	Grants in $t+1$	Grants in $t+1$	VC investment	VC investment	VC investment
VC investment	0.267 (0.20)	0.598 (0.20) <sup>***</sup>	0.445 (0.25) <sup>*</sup>			
Patent applications (Log)	0.513 (0.13) <sup>***</sup>		0.627 (0.14) <sup>***</sup>	−0.094 (0.08)		
Patent applications > 0	0.980 (0.22) <sup>***</sup>		1.594 (0.23) <sup>***</sup>	0.574 (0.20) <sup>***</sup>		
Patent grants (log)		0.584 (0.16) <sup>***</sup>			−0.166 (0.12)	
Patent grants > 0		1.182 (0.22) <sup>***</sup>			0.393 (0.23) <sup>*</sup>	
Age (log)	0.164 (0.07) <sup>**</sup>	0.073 (0.09)	0.167 (0.09) <sup>*</sup>	−0.331 (0.09) <sup>***</sup>	−0.345 (0.09) <sup>***</sup>	−0.339 (0.09) <sup>***</sup>
Size (log(employees + 1))	0.123 (0.06) <sup>**</sup>	0.028 (0.06)	−0.012 (0.07)	0.202 (0.07) <sup>***</sup>	0.205 (0.06) <sup>***</sup>	0.193 (0.07) <sup>***</sup>
U.S. firm	0.132 (0.14)	0.344 (0.15) <sup>**</sup>	0.409 (0.18) <sup>**</sup>	−0.327 (0.14) <sup>**</sup>	−0.324 (0.14) <sup>**</sup>	−0.323 (0.14) <sup>**</sup>
Medium-high tech manuf.	0.177 (0.32)	−0.045 (0.34)	−0.202 (0.27)	−0.235 (0.29)	−0.138 (0.29)	−0.142 (0.29)
Medium-low tech manuf.	−0.127 (0.32)	−0.407 (0.35)	−0.500 (0.28) <sup>*</sup>	−0.405 (0.29)	−0.351 (0.30)	−0.347 (0.29)
R&D services & software	−0.235 (0.36)	−0.229 (0.39)	−0.352 (0.36)	0.259 (0.29)	0.312 (0.30)	0.312 (0.30)
Other services	0.122 (0.34)	−0.761 (0.40) <sup>*</sup>	−0.786 (0.36) <sup>**</sup>	−0.127 (0.31)	−0.084 (0.31)	−0.099 (0.31)
R&D expend. (yes/no)	0.430 (0.18) <sup>**</sup>	0.278 (0.20)	0.432 (0.22) <sup>**</sup>	0.419 (0.21) <sup>**</sup>	0.442 (0.21) <sup>**</sup>	0.464 (0.21) <sup>**</sup>
R&D staff (in %)	0.170 (0.36)	0.563 (0.46)	−0.352 (0.46)	0.696 (0.33) <sup>**</sup>	0.878 (0.32) <sup>***</sup>	0.874 (0.31) <sup>***</sup>
CEO has a degree	0.085 (0.14)	−0.261 (0.16) <sup>*</sup>	−0.288 (0.18)	0.335 (0.17) <sup>**</sup>	0.339 (0.17) <sup>**</sup>	0.362 (0.17) <sup>**</sup>
Market size	0.239 (0.09) <sup>***</sup>	0.300 (0.10) <sup>***</sup>	0.260 (0.11) <sup>***</sup>	0.198 (0.09) <sup>**</sup>	0.196 (0.09) <sup>**</sup>	0.214 (0.09) <sup>**</sup>
Product dev. time	0.163 (0.06) <sup>***</sup>	0.136 (0.07) <sup>**</sup>	0.119 (0.08)	0.044 (0.07)	0.053 (0.07)	0.057 (0.07)
Competitors (log)	−0.119 (0.06) <sup>*</sup>	−0.111 (0.07) <sup>*</sup>	−0.202 (0.08) <sup>***</sup>	−0.077 (0.07)	−0.089 (0.07)	−0.092 (0.07)
Intercept	−3.311 (0.46) <sup>***</sup>	−2.448 (0.52) <sup>***</sup>	−2.588 (0.52) <sup>***</sup>	−1.883 (0.44) <sup>***</sup>	−1.887 (0.44) <sup>***</sup>	−1.889 (0.44) <sup>***</sup>
Observations	940	940	940	940	940	940
Log-Likelihood	−252.3	−218.3	−159.3	−235.2	−237.1	−238.9
Chi-sq. test	235.7	186.4	265.8	111.0	114.6	101.5
p-Value	0.000	0.000	0.000	0.000	0.000	0.000
Pseudo-R <sup>2</sup>	0.428	0.451	0.599	0.241	0.235	0.229

Notes. This table presents probit models for the likelihood of observing any number of patent applications or grants, respectively, in columns 1–3 and probit models for the likelihood of observing venture capital investments in columns 4–6. Robust standard errors are in parentheses.

Significance levels: \*\*\*  $p < 0.01$ ; \*\*  $p < 0.05$ ; \*  $p < 0.1$ .

**Table 7**

Likelihood of becoming a merger or acquisition target.

Dependent variable	M&A Target		M&A Target	
Model	1	2	3	4
VC investment $\times$ applications (log)			−0.013 (0.19)	
VC investment $\times$ grants (log)				0.303 (0.26)
VC investment $\times$ (applications > 0)	−0.433 (0.38)		−0.406 (0.55)	
VC investment $\times$ (grant > 0)		−0.215 (0.39)		−0.700 (0.55)
VC investment	0.619 (0.24)**	0.547 (0.23)**	0.619 (0.24)**	0.537 (0.23)**
Patent applications (log)	0.020 (0.09)		0.024 (0.11)	
Patent applications > 0	0.509 (0.26)**		0.502 (0.27)*	
Patent grants (log)		0.183 (0.12)		0.108 (0.13)
Patent grants > 0		0.184 (0.28)		0.302 (0.28)
Age (log)	−0.181 (0.09)**	−0.191 (0.09)**	−0.181 (0.09)**	−0.190 (0.09)**
Size (log(employees + 1))	0.266 (0.07)***	0.257 (0.06)***	0.266 (0.07)***	0.257 (0.06)***
U.S. firm	−0.124 (0.15)	−0.143 (0.15)	−0.125 (0.14)	−0.145 (0.15)
Medium-high tech manuf.	−0.157 (0.33)	−0.134 (0.33)	−0.157 (0.33)	−0.171 (0.33)
Medium-low tech manuf.	−0.257 (0.34)	−0.234 (0.34)	−0.258 (0.34)	−0.258 (0.34)
R&D services & software	−0.289 (0.37)	−0.294 (0.36)	−0.292 (0.36)	−0.278 (0.36)
Other services	−0.525 (0.37)	−0.514 (0.37)	−0.525 (0.37)	−0.527 (0.37)
R&D expend. (yes/no)	−0.507 (0.18)***	−0.474 (0.18)***	−0.506 (0.18)***	−0.475 (0.18)***
R&D staff (in %)	0.218 (0.44)	0.133 (0.46)	0.216 (0.44)	0.127 (0.46)
CEO has a degree	0.132 (0.17)	0.150 (0.18)	0.133 (0.17)	0.146 (0.18)
Market size	0.119 (0.08)	0.129 (0.08)	0.118 (0.08)	0.139 (0.08)*
Product dev. time	0.072 (0.08)	0.067 (0.08)	0.072 (0.08)	0.066 (0.08)
Competitors (log)	−0.055 (0.08)	−0.051 (0.08)	−0.055 (0.08)	−0.050 (0.07)
Intercept	−2.004 (0.43)***	−1.958 (0.42)***	−2.001 (0.43)***	−1.952 (0.43)***
Observations	940	940	940	940
Log-Likelihood	−170.713	−171.065	−170.711	−170.518
Chi-sq. test	65.850	64.510	66.040	65.380
p-Value	0.000	0.000	0.000	0.000
Pseudo- $R^2$	0.151	0.149	0.151	0.152

Significance levels: \*\*\*  $p < 0.01$ ; \*\*  $p < 0.05$ ; \*  $p < 0.1$ .

## 5.2. Sample attrition bias

Sample attrition can be a problem if firms disappearing in period  $t + 1$  are systematically those for which venture capital investment had a positive effect on patenting. To limit the risk of attrition bias we investigate the merger and acquisition history of the firms in our sample by retrieving the relevant records from Thomson Reuters' SDC Platinum database. We use this information to estimate the probability that firms are acquired depending on whether they patent and whether they receive VC funding. Table 7 shows that firms are more likely to be acquired if they patent in period  $t$  and if they experience VC investment. This result is not surprising since acquirers may follow the same patent signals that cause venture capitalists to invest—or may even be venture capitalists themselves. Note, however, that the interaction effects for VC investment and patenting are not significant. Sample attrition due to mergers and acquisitions, if these firms actually leave the sample, is thus unlikely to systematically reduce the measured effect of VC on patenting.

After inspecting the M&A records in the SDC database, if a firm is the target of any kind of transaction, we correct the number of patent applications and grants in the following way. If a firm retains its identity and remains active under its name in the sample, we keep the original number of patents. An example of this type of transaction is a leveraged buyout, in which the firm's management acquires the firm, but the operating business remains unchanged. If, instead, the firm is merged into the acquirer, we check whether it is still patenting at the original location, but under the acquirer's name, and if this is the case we add these patents to the sample. If the firm disappears as a legal entity after the merger, we add all the acquirer's patents to the original firm's patents, which then establishes an upper boundary for the firms' patenting activity in  $t + 1$ . Of 128 transactions we identified, we adjusted the patent application or grant numbers for 15 firms. The results of the binary models presented in Table 8 are unchanged, while those of the zero-inflated Poisson models presented in Table 9 show an insignificant effect of

VC on patenting in models 1 and 3, as one might confidently expect after attributing merged firms' technological outputs into those of acquiring firms.

## 5.3. Formal vs. informal venture capital

Pooling formal and informal VC investments in our model may affect results if the two classes of investors behave differently in relation to the technological profiles of their investee firms. Out of 96 firms that obtain VC financing in our sample, 66 firms receive formal VC funding, while 41 firms attract VC investors. We therefore disaggregate formal VC investments from those of informal venture capitalists (such as business angels) in Table 10, but find the results for the two sub-samples to be very similar. Effects of VC involvement are negative in both cases, albeit insignificant, while the effect of formal VC on patenting seems to be more negative than that of informal VC. While these effects do not seem to differ between types of investors, their lack of significance is an expected consequence of the reduced number of observations in each binary model estimation.

It should also be pointed out that the effects observed in Table 10 may be due to the fact that the control groups for firms that gained formal (or informal) venture capital include firms financed by informal (or formal) venture capital. Hence, we would (to some extent) be comparing firms receiving formal and informal venture capital and not, for example, firms gaining formal venture capital with those receiving neither type of investment. If we exclude firms funded by informal VC from the control group for the formal VC models, and vice versa, we find that these effects remain insignificant and qualitatively unchanged from those presented in Table 10. These robustness checks, which take into account the type of VC investor, contrast with Conti et al.'s (2013a) results, where business angels are found not to be as sensitive as VC to patent signals, but are consistent with results presented by Audretsch et al. (2012), whose estimations of probit models for the probability of receiving



**Table 8**  
Patenting and VC investment—simultaneous equations, adjusted for M&A.

Dependent variable in patenting equation	Applications in $t + 1$		Grants in $t + 1$		Grants in $t + 1$	
Model	1		2		3	
Dependent variable in patenting equation	Patenting (yes/no)	VC investment	Patenting (yes/no)	VC investment	Patenting (yes/no)	VC investment
VC investment	−0.758 (0.35)**		−0.271 (0.51)		−0.489 (0.35)	
Patent applications (log)	0.467 (0.13)***	−0.092 (0.08)			0.561 (0.13)***	−0.098 (0.08)
Patent applications > 0	1.044 (0.21)***	0.607 (0.20)***			1.582 (0.22)***	0.622 (0.20)***
Patent grants (log)			0.523 (0.16)***	−0.170 (0.12)		
Patent grants > 0			1.166 (0.22)***	0.445 (0.23)*		
Age (log)	0.055 (0.08)	−0.348 (0.10)***	−0.005 (0.11)	−0.346 (0.09)***	0.069 (0.10)	−0.345 (0.09)***
Size (log(employees + 1))	0.166 (0.06)***	0.199 (0.07)***	0.081 (0.07)	0.213 (0.07)***	0.058 (0.07)	0.205 (0.07)***
U.S. firm	0.068 (0.13)	−0.334 (0.13)**	0.244 (0.16)	−0.324 (0.14)**	0.273 (0.17)	−0.328 (0.14)**
Medium-high tech manuf.	0.129 (0.29)	−0.222 (0.29)	−0.061 (0.34)	−0.215 (0.30)	−0.204 (0.27)	−0.258 (0.28)
Medium-low tech manuf.	−0.163 (0.29)	−0.382 (0.29)	−0.450 (0.35)	−0.403 (0.29)	−0.534 (0.27)*	−0.412 (0.28)
R&D services & software	−0.146 (0.32)	0.273 (0.30)	−0.139 (0.40)	0.266 (0.29)	−0.245 (0.35)	0.261 (0.29)
Other services	0.072 (0.31)	−0.097 (0.31)	−0.755 (0.40)*	−0.136 (0.31)	−0.765 (0.35)**	−0.137 (0.31)
R&D expend. (yes/no)	0.504 (0.18)***	0.426 (0.21)**	0.349 (0.19)*	0.436 (0.21)**	0.499 (0.20)**	0.423 (0.22)*
R&D staff (in %)	0.387 (0.36)	0.693 (0.33)**	0.742 (0.44)*	0.829 (0.32)***	−0.162 (0.44)	0.643 (0.33)*
CEO has a degree	0.198 (0.14)	0.365 (0.17)**	−0.180 (0.16)	0.354 (0.17)**	−0.188 (0.17)	0.352 (0.17)**
Market size	0.263 (0.08)***	0.190 (0.09)**	0.335 (0.10)***	0.201 (0.09)**	0.301 (0.10)***	0.204 (0.09)**
Product dev. time	0.166 (0.06)***	0.037 (0.07)	0.137 (0.06)**	0.053 (0.07)	0.118 (0.07)	0.042 (0.07)
Competitors (log)	−0.127 (0.06)**	−0.087 (0.08)	−0.131 (0.06)**	−0.085 (0.08)	−0.215 (0.07)***	−0.073 (0.07)
Intercept	−3.096 (0.46)***	−1.831 (0.45)***	−2.354 (0.53)***	−1.889 (0.43)***	−2.482 (0.51)***	−1.888 (0.43)***
Observations	940		940		940	
Log-likelihood	−489.7		−459.4		−399.7	
Chi-sq. test	348.2		295.7		369.9	
p-Value	0.000		0.000		0.000	
$\rho(v_{it}, \omega_{it})$	0.567		0.484		0.530	
p-Value for $\rho$ (Wald test)	0.011		0.091		0.001	
Pseudo- $R^2$	0.313		0.355		0.439	

Notes. This table presents bivariate recursive probit models for patent applications, patent grants and for the likelihood of observing venture capital investments. Robust standard errors are in parentheses. Significance levels: \*\*\*  $p < 0.01$ ; \*\*  $p < 0.05$ ; \*  $p < 0.1$ .

**Table 9**  
Patenting, patent numbers, and VC investment—Adjusted for M&A.

Dependent variable in patenting equations	Applications in $t + 1$		Grants in $t + 1$		Grants in $t + 1$	
Model	1		2		3	
Dependent variable	Not patenting (zero inflation)	VC investment	Not patenting (zero inflation)	VC investment	Not patenting (zero inflation)	VC investment
VC investment	0.942 (0.65)		−0.435 (0.58)		−0.295 (0.81)	
Patent applications (log)	−0.257 (0.36)	−0.088 (0.09)			−0.413 (0.21)**	−0.095 (0.09)
Patent applications > 0	−2.406 (0.98)**	0.583 (0.20)***			−2.508 (0.57)***	0.590 (0.21)***
Patent grants (log)			−0.539 (0.18)***	−0.169 (0.11)		
Patent grants > 0			−1.130 (0.25)***	0.421 (0.22)*		
Age (log)	−0.116 (0.16)	−0.352 (0.10)***	−0.137 (0.11)	−0.342 (0.09)***	−0.046 (0.15)	−0.332 (0.09)***
Size (log(employees + 1))	−0.255 (0.13)**	0.203 (0.07)***	−0.012 (0.08)	0.208 (0.07)***	−0.020 (0.10)	0.204 (0.07)***
U.S. firm	0.181 (0.27)	−0.329 (0.13)**	−0.345 (0.17)**	−0.313 (0.14)**	−0.251 (0.24)	−0.323 (0.14)**
Medium-high tech manuf.	−0.218 (0.52)	−0.217 (0.29)	0.001 (0.44)	−0.144 (0.29)	0.178 (0.40)	−0.243 (0.28)
Medium-low tech manuf.	0.173 (0.54)	−0.377 (0.29)	0.471 (0.45)	−0.358 (0.29)	0.578 (0.41)	−0.416 (0.28)
R&D services & software	0.052 (0.59)	0.276 (0.30)	0.177 (0.51)	0.319 (0.30)	−0.075 (0.45)	0.253 (0.29)
Other services	−0.666 (0.66)	−0.098 (0.31)	0.791 (0.50)	−0.085 (0.31)	0.902 (0.57)	−0.148 (0.30)
R&D expend. (yes/no)	−0.821 (0.34)**	0.422 (0.21)**	−0.395 (0.22)*	0.440 (0.21)**	−0.608 (0.32)*	0.414 (0.21)*
R&D staff (in %)	0.325 (0.68)	0.703 (0.33)**	−0.496 (0.53)	0.877 (0.32)***	1.085 (0.63)*	0.674 (0.33)**
CEO has a degree	−0.486 (0.27)*	0.350 (0.17)**	0.210 (0.20)	0.323 (0.17)*	0.274 (0.24)	0.336 (0.17)**
Market size	−0.405 (0.16)**	0.188 (0.09)**	−0.288 (0.12)**	0.208 (0.09)**	−0.396 (0.17)**	0.204 (0.09)**
Product dev. time	−0.246 (0.11)**	0.038 (0.07)	−0.143 (0.08)*	0.052 (0.07)	−0.215 (0.12)*	0.040 (0.07)
Competitors (log)	0.178 (0.10)*	−0.090 (0.08)	0.140 (0.08)*	−0.083 (0.07)	0.189 (0.12)	−0.076 (0.08)
Intercept	4.270 (0.92)***	−1.815 (0.44)***	2.386 (0.62)***	−1.936 (0.44)***	2.680 (0.70)***	−1.885 (0.44)***
Dependent variable	Patents (number)		Patents (number)		Patents (number)	
VC investment	−0.224 (0.42)		0.466 (0.21)**		0.076 (0.20)	
Patent applications (Log)	0.922 (0.09)***				0.935 (0.07)***	
Patent applications > 0	−0.444 (0.34)				−0.651 (0.32)**	
Patent grants (log)			0.580 (0.07)***			
Patent grants > 0			0.607 (0.20)***			
Age (log)	−0.061 (0.14)		−0.281 (0.11)***		0.071 (0.12)	
Size (log(employees + 1))	−0.050 (0.08)		0.201 (0.08)**		0.025 (0.12)	
U.S. firm	0.422 (0.25)*		−0.017 (0.19)		0.217 (0.17)	
Medium-high tech manuf.	−0.037 (0.65)		0.053 (0.69)		0.383 (0.43)	
Medium-low tech manuf.	0.108 (0.72)		0.366 (0.71)		0.579 (0.42)	
R&D services & software	−0.415 (0.58)		−0.196 (0.72)		−0.111 (0.43)	
Other services	−1.100 (0.81)		−0.091 (0.77)		0.223 (0.87)	
R&D expend. (yes/no)	0.203 (0.61)		−0.396 (0.39)		0.352 (0.67)	

Table 9 (Continued)

Dependent variable	Patents (number)	Patents (number)	Patents (number)
R&D staff (in %)	0.930 (0.33)***	0.755 (0.29)**	0.877 (0.33)***
CEO has a degree	−0.240 (0.22)	−0.174 (0.34)	−0.066 (0.22)
Market size	−0.040 (0.09)	0.258 (0.11)**	−0.147 (0.13)
Product dev. time	0.051 (0.05)	0.035 (0.07)	−0.050 (0.08)
Competitors (log)	−0.095 (0.05)*	0.025 (0.12)	−0.252 (0.12)**
Intercept	0.526 (0.75)	0.043 (0.77)	0.106 (0.71)
Var( $\omega_{it}$ )	1.396 (0.26)***	0.594 (0.09)***	0.493 (0.08)***
$\rho(v_{it}, \varepsilon_{it})$	−0.625 (0.14)***	−0.136 (0.27)	−0.353 (0.36)
$\rho(v_{it}, \omega_{it})$	0.018 (0.06)	−0.379 (0.06)***	−0.311 (0.03)***
Observations	940	940	940
Wald test	18828	20622	17408
p-Value	0.000	0.000	0.000
Log-likelihood	−1002.1	−866.2	−786.5

Notes. This table presents zero-inflated Poisson models for patent applications and patent grants during the period following the survey period, including an endogenous equation for venture capital investment. Robust standard errors (estimated using the sandwich estimator) are shown in parentheses.

Significance levels: \*\*\*  $p < 0.01$ ; \*\*  $p < 0.05$ ; \*  $p < 0.1$ .

Table 10

Formal vs. informal venture capital.

Model	Venture capital investment			Informal VC investment		
	1	2	3	4	5	6
Dependent variable in patenting equation	Applications in $t+1$	Grants in $t+1$	Grants in $t+1$	Applications in $t+1$	Grants in $t+1$	Grants in $t+1$
Patenting (yes/no)						
VC investment	−0.676 (0.45)	−0.957 (0.82)	−1.039 (1.13)			
Informal VC investment				−0.614 (0.77)	0.588 (0.87)	−0.152 (0.49)
Patent applications (log)	0.468 (0.12)***		0.538 (0.17)***	0.488 (0.14)***		0.585 (0.13)***
Patent applications > 0	1.057 (0.20)***		1.601 (0.25)***	1.031 (0.22)***		1.636 (0.22)***
Patent grants (log)		0.476 (0.17)***			0.598 (0.17)***	
Patent grants > 0		1.179 (0.25)***			1.208 (0.22)***	
Age (log)	0.099 (0.08)	−0.043 (0.13)	0.047 (0.16)	0.125 (0.08)	0.060 (0.10)	0.144 (0.09)
Size (log(employees + 1))	0.155 (0.06)***	0.092 (0.08)	0.062 (0.10)	0.134 (0.06)**	0.049 (0.06)	0.003 (0.07)
U.S. firm	0.071 (0.14)	0.188 (0.21)	0.265 (0.24)	0.086 (0.14)	0.335 (0.15)**	0.359 (0.18)**
Medium-high tech manuf.	0.079 (0.30)	−0.178 (0.32)	−0.340 (0.27)	0.176 (0.30)	−0.118 (0.34)	−0.191 (0.28)
Medium-low tech manuf.	−0.233 (0.31)	−0.538 (0.32)*	−0.638 (0.27)**	−0.138 (0.31)	−0.486 (0.35)	−0.492 (0.28)*
R&D services & software	−0.171 (0.33)	−0.127 (0.37)	−0.243 (0.35)	−0.135 (0.35)	−0.201 (0.39)	−0.234 (0.35)
Other services	0.067 (0.32)	−0.709 (0.40)*	−0.759 (0.34)**	0.133 (0.33)	−0.855 (0.40)**	−0.757 (0.35)**
R&D expend. (yes/no)	0.456 (0.18)**	0.357 (0.19)*	0.471 (0.20)**	0.460 (0.19)**	0.267 (0.20)	0.447 (0.21)**
R&D staff (in %)	0.336 (0.34)	0.870 (0.41)**	−0.013 (0.49)	0.264 (0.36)	0.693 (0.45)	−0.214 (0.43)
CEO has a degree	0.110 (0.14)	−0.166 (0.16)	−0.210 (0.18)	0.134 (0.15)	−0.273 (0.16)*	−0.237 (0.18)
Market size	0.271 (0.09)***	0.350 (0.09)***	0.317 (0.11)***	0.242 (0.09)***	0.329 (0.11)***	0.263 (0.11)**
Product dev. time	0.151 (0.06)**	0.121 (0.07)*	0.109 (0.07)	0.172 (0.06)**	0.132 (0.07)*	0.130 (0.08)*
Competitors (log)	−0.126 (0.06)**	−0.122 (0.06)**	−0.193 (0.08)**	−0.121 (0.06)**	−0.117 (0.07)*	−0.207 (0.08)***
Intercept	−3.129 (0.46)***	−2.166 (0.53)***	−2.352 (0.56)***	−3.223 (0.46)***	−2.434 (0.52)***	−2.567 (0.52)***
VC/Inf. VC investment						
Patent applications (log)	−0.070 (0.09)		−0.082 (0.09)	−0.269 (0.10)***		−0.264 (0.10)***
Patent applications > 0	0.701 (0.22)***		0.749 (0.27)***	0.583 (0.24)**		0.600 (0.23)**
Patent grants (log)		−0.054 (0.12)			−1.212 (0.38)***	
Patent grants > 0		0.507 (0.25)**			0.457 (0.32)	
Age (log)	−0.337 (0.11)***	−0.318 (0.10)***	−0.326 (0.10)***	−0.318 (0.13)**	−0.354 (0.12)***	−0.330 (0.13)***
Size (log(employees + 1))	0.250 (0.07)***	0.267 (0.08)***	0.269 (0.07)***	0.036 (0.09)	0.049 (0.09)	0.032 (0.09)
U.S. firm	−0.265 (0.16)*	−0.282 (0.16)*	−0.287 (0.16)*	−0.354 (0.17)**	−0.341 (0.17)*	−0.341 (0.17)**
Medium-high tech manuf.	−0.437 (0.31)	−0.479 (0.35)	−0.493 (0.34)	0.206 (0.50)	0.328 (0.53)	0.223 (0.49)
Medium-low tech manuf.	−0.501 (0.33)	−0.564 (0.33)*	−0.556 (0.32)*	0.062 (0.51)	0.155 (0.52)	0.097 (0.49)
R&D services & software	0.123 (0.33)	0.091 (0.33)	0.095 (0.33)	0.491 (0.49)	0.542 (0.51)	0.547 (0.48)
Other services	−0.070 (0.34)	−0.176 (0.34)	−0.145 (0.34)	0.276 (0.52)	0.362 (0.54)	0.303 (0.51)
R&D expend. (yes/no)	0.352 (0.24)	0.350 (0.25)	0.350 (0.27)	0.664 (0.29)**	0.703 (0.30)**	0.691 (0.30)**
R&D staff (in %)	0.835 (0.35)**	0.868 (0.33)***	0.765 (0.36)**	0.012 (0.46)	0.318 (0.46)	−0.012 (0.45)
CEO has a degree	0.122 (0.19)	0.105 (0.20)	0.110 (0.19)	0.622 (0.22)***	0.625 (0.22)***	0.636 (0.22)***
Market size	0.344 (0.10)***	0.357 (0.11)***	0.366 (0.10)***	−0.016 (0.11)	−0.022 (0.10)	−0.004 (0.11)
Product dev. time	−0.011 (0.08)	−0.002 (0.08)	−0.016 (0.09)	0.138 (0.08)*	0.175 (0.08)**	0.142 (0.08)*
Competitors (log)	−0.084 (0.08)	−0.080 (0.08)	−0.081 (0.09)	−0.049 (0.09)	−0.079 (0.10)	−0.036 (0.09)
Intercept	−2.342 (0.52)***	−2.372 (0.53)***	−2.431 (0.51)***	−2.152 (0.68)***	−2.171 (0.68)***	−2.237 (0.66)***
Observations	940	940	940	940	940	940
Log-likelihood	−425.3	−396.6	−333.1	−391.7	−350.6	−297.0
Chi-sq. test	338.5	312.7	336.6	303.9	270.3	370.7
p-Value	0.000	0.000	0.000	0.000	0.000	0.000
$\rho(v_{it}, \varepsilon_{it})$	0.524	0.756	0.735	0.354	0.140	0.382
p-Value for $\rho$ (Wald test)	0.038	0.320	0.421	0.387	0.737	0.019
Pseudo- $R^2$	0.378	0.382	0.481	0.319	0.342	0.443

Notes. This table presents zero-inflated Poisson models for patent applications and patent grants during the period following the survey period, including an endogenous equation for venture capital investment. Robust standard errors (estimated using the sandwich estimator) are shown in parentheses.

Significance levels: \*\*\*  $p < 0.01$ ; \*\*  $p < 0.05$ ; \*  $p < 0.1$ .

formal or informal VC investments show no substantial differences between the reactions of the two to patent signals. At this stage, this remains an interesting question for further investigation.

#### 5.4. Identification and alternative control variables

Estimation results for the patenting equations in our bivariate and trivariate models depend on the correct specification of the venture capital equation describing the selection of investments by VC investors. We test two alternative specifications to address potential model misspecification. First, we replace logarithmic age and size with quadratic specifications, as is customary in some of the literature on small and medium-sized enterprises. Second, we test our main models with two extra regressors in the venture capital equation to strengthen identification of the model.

When we re-run the models in [Tables 3 and 4](#), all results for the effect of VC investment on patent applications and grants continue to hold. Adding four extra terms to the bivariate model (squared age and size in both equations) and six new terms to the trivariate models may be a cause for concern about over-specification, and about whether these extra terms add explanatory power. A direct comparison of quadratic specifications against the baseline models using Akaike's information criterion (AIC) suggests that quadratic specifications perform either as well as (in models with patent grants) or worse (in models with patent applications) than the baseline model with logarithmic controls.

Models identified by functional form, such as the simultaneous models tested in this paper, may be sensitive to error terms' deviations from normality. An exclusion restriction in the patenting equation(s) can help to identify the coefficients in the model, if a variable can be found that explains VC investment but not patenting outcomes. The survey dataset used in this paper includes two such variables. Respondents are asked on a five-point Likert scale whether they expect the firm's turnover will be smaller or larger in ten years' time, and a similar question is asked about the firm's market value. When we add both variables measuring expectations about future growth to the VC equations in [Tables 3 and 4](#), they jointly explain VC at the 5% significance level, which is plausible given that high-growth firms are likely investment targets of VC funds. A firm's patenting behaviour is not expected to be driven by growth options, but rather by the appropriability of its technology and the indicators for market structure that we use in our models. Results including these two regressors in the VC equation are qualitatively identical to our main results. Almost all coefficients that were originally significant at the 5% level remain significant at that level. Only two differences can be found: market size in the patenting equation in model 1 in [Table 3](#) and product development time in model 1 in [Table 4](#) are both now significant at the 10% level. We conclude that our results are robust against the two risks of model misspecification tested here<sup>13</sup>.

## 6. Conclusion

The mechanisms by which firms signal their quality to investors through patents and how venture capital funds influence these firms' patenting behaviours have been studied in the literature, but have rarely been linked to one another. We argue that, as firms' patenting activities might depend on venture capitalists' decisions to invest based on patent signals, these two decisions should be investigated simultaneously instead of separately. In this paper, we model firms' patenting behaviours explicitly allowing for the endogeneity of VC investments. Incorporating investors' decisions

into a simultaneous model is necessary to disentangle investment selection from technological value-adding (or coaching) effects.

In contrast to the findings of studies on aggregate patenting and VC investment, we find that the causal link between VC and patenting is weak, at best. A positive effect can only be found if the potential endogeneity of VC financing is ignored. Instead, we find that VC even exerts a negative influence on investee firms' future patent applications and grants. This suggests that, by limiting the dispersion of inventive efforts that often characterise inexperienced firms, venture capitalists help portfolio companies to rationalise their technology searches and focus on the opportunities with the highest commercial potential. This result is plausible and compatible with the expectations of behavioural theories of the firm that take into account the cognitive limitations of economic agents and stress the importance of the allocation of resources – such as managerial attention – to selected aspect of the business ([Simon, 1947](#); [Weick, 1979](#); [Ocasio, 1997, 2011](#)). A small but growing firm may have developed valuable IP and attracted external finance on this basis—but, at this point, a trade-off emerges between sustaining or increasing the level of knowledge creation activities (invention) and capitalizing on existing assets. This can include commercialisation activities such as marketing, or operational activities such as the scaling up of production. Evidence of unchanged or decreasing technological output after VC investment can therefore be interpreted as a positive development for the firm's growth prospects. Venture capitalists do not contribute to a firm's growth by augmenting its inventive potential: the firm in which they invest is already good at generating new knowledge, which is why they have selected it (on the basis of patent signals). This is also compatible with the view that venture capitalists are 'impatient' investors: they can come in after initial R&D costs have been sunk and negotiate with cash poor and knowledge rich firms with an emphasis on later stage and more tangible outputs<sup>14</sup>.

Venture capital investments affect firms' growth paths by re-orienting their resources towards the exploitation of existing technological knowledge: they act as focusing devices in the process of entrepreneurial growth. Is it possible that venture capitalists might want to increase the firm's knowledge stock to increase its liquidation value should the business fail? Evidence from a recent survey of US venture capitalists, run by the National Venture Capital Association, confirms that this is indeed not the objective of investors ([Feldman, 2013](#)), aligning strongly with our results.

When we consider the co-determinants of patenting, we find that firm size is positively related to future patent applications. R&D efforts measured by the existence of R&D expenses and the percentage of R&D staff are highly significant. Where [Baum and Silverman \(2004\)](#) find mixed evidence for an age effect on applications and grants, we decompose this effect into a non-significant one on the likelihood to patent, and a potentially negative one on the number of grants obtained. We find that having an R&D programme determines whether a firm patents at all, while the proportion of scientific staff explains the number of patent applications and grants. Finally, the effect of industry competition on the intensity of patenting is negative, and product development times and market size are both positive predictors of patenting activity.

VC funds select portfolio companies based on the signalling function of patents. Interestingly, while such investors are attracted to patent-active firms, they show only weak sensitivity to the number of patents, which might again indicate a preference for focus

<sup>13</sup> The results from all these robustness tests are available from the authors on request.

<sup>14</sup> We are grateful to an anonymous referee for pressing us on this issue and for suggesting the alternative explanation. The problem of VC as 'impatient capital' has been recently discussed by [Mazzucato \(2013\)](#) and [Crafts and Hughes \(2013\)](#). The stage distribution of VC investments is analysed in some detail by [Lahr and Mina \(2014\)](#).

rather than (possibly over-dispersed) search activities. By modelling the venture capitalists' decision to invest and the portfolio company's patenting activity simultaneously, we find that patenting has much sharper effects on VC investments than the other way round. The coaching function of VC concerns the commercialisation of a firm's existing patents or contributes to the rationalisation of its patenting activities. This also indicates that, in this context, innovation – interpreted as the Schumpeterian application of invention to market need – may be promoted not by more, but by less patenting after external investment.

From a technical viewpoint, our models greatly reduce the chances that selection by venture capitalists might drive a change in observed patenting behaviours, because estimating the correlation between the error terms in both equations controls for unobserved simultaneous variance in VC financing and patenting. If VC reacts to some unobserved company characteristic that can be subsumed within the error term of the switching equation, this unobserved heterogeneity is taken into account when estimating the outcome model for patenting activity. Error correlations between the venture capital and patenting equations are significant and substantial, which supports our estimation strategy and further strengthens the case for this study's methodological approach. Further research – possibly with larger samples, while controlling for selection effects – could generate additional quantitative evidence on the effect of a VC's coaching function on different aspects – or stages – of the technology life cycle. This may also include identifying implications for short and long-run firm performance, conditional on the joint dynamics of patenting and financing.

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